Resource allocation in the brain and the equity premium puzzle

Siddiqi, Hammad

1 February 2020

Resource Allocation in the Brain and the Equity Premium Puzzle

Hammad Siddiqi

University of the Sunshine Coast

hsiddiqu@usc.edu.au

This Version: Feb. 1, 2020

Abstract

What happens when information reaches the human brain? In economics, a black box approach to information absorption is generally taken with an implicit assumption that, information, once it reaches the brain, is correctly processed. In sharp contrast, research in brain sciences has established that when information reaches the brain, a pre-existing knowledge structure or schema is first activated, which influences information absorption. The process through which these knowledge structures are created is resource intensive. It involves using a pre-existing schema as a starting point and attempting to adjust it appropriately by using finite brain resources. We apply this approach to the thinking process of investors trying to work out the worth of various stocks. We show that with a binding resource constraint, a new multiplicative term emerges on the right-hand-side of the standard Sharpe-ratio expression in asset pricing. This new term provides a unified explanation for the equity premium puzzle, generates countercyclical equity premia, and gives rise to size, value, and momentum effects. A novel prediction of the approach is negative correlation of momentum with value and size.

JEL Classification G12, G10

Key Words: Equity Premium Puzzle, Value Effect, Momentum Effect, Size Effect, Countercyclical Equity Premia, Schema, Resource Allocation

Resource Allocation in the Brain and the Equity Premium Puzzle

When happens when information reaches the brain? In economics, a black box approach to information absorption is generally taken with an implicit assumption that, information, once it reaches the brain, is correctly absorbed. In sharp contrast, research in brain sciences has established that, when information reaches the brain, some relevant pre-existing knowledge structure (referred to as a schema) is activated, which plays a critical role in how the new information is absorbed.[1] How are these pre-existing knowledge structures or schemas created? Brain imaging studies show that schema construction is a resource-intensive process that involves different regions of the brain talking to each other[2]; however, these schemas, once formed, make subsequent processing of schema-consistent information a lot faster.[3] Schemas, once established, are resistant to change and many large prediction errors are necessary before a change is considered.[4] In this article, we incorporate this richer view from brain sciences into asset pricing, and show that a plausible resolution of the equity premium puzzle emerges. The approach developed here leads to equity premia that are countercyclical along with features akin to size, value, and momentum effects. A novel prediction of the approach is as follows: Momentum effect is negatively correlated with value and size.

A schema is a pre-existing knowledge structure that serves as a scaffold or a blueprint.[5] Neurologically, it is a brain template that involves systems of neurons across various brain regions talking to each other, with each system constituting a particular unit in the schema. That is, schemas contain units as well as relationships between these units. For example, for a car schema, units could be car body and wheel, with the relationship that car body contains four wheels. For a family schema, the units could be two adults and children with the relationship that adults are parents of children. Schemas, by only containing the essential details, simplify the world. They direct attention to relevant aspects, and speed-up processing of information that fits within the schema.

[1] There is a large body of literature in neuroscience that explores various facets of schemas and how they influence information absorption (for a review, see van Kesteren et al (2012), Gilboa and Marlatte (2017), Spalding et al (2015) and references therein).
[2] See Ohki and Takei (2018) and references therein.
[3] Sweegers et al (2015), van Kesteren et al (2014)
[4] See van Kesteren and Meeter (2020) for a review of relevant neuroscience research.
[5] See Hampson and Morris (1996) or Anderson (2000) for a detailed review of schema theory.

Brain only weighs about 2% of the body weight; however, it consumes over 20% of body's energy intake. A third of brain's energy need is spent on brain cell and tissue maintenance, with the remaining two-third (13% - 14% of body's typical energy intake) allocated to information processing. However, considerably less brain resources are needed for information that fits within an existing schema.[6] Information that does not fit within any pre-existing schema is likely to be ignored; however, if its salience does not allow it to be ignored, then a new schema may be constructed. Schema construction is a resource intensive process, with the brain typically using a related pre-existing schema as a starting point and then spending resources in an attempt to appropriately adjust it. For example, a child initially may only have a horse schema (large with four legs and a tail). However, if she encounters a cow, then the horse schema may be modified to create a cow schema. Brain organizes knowledge in a series of such inter-connected schemas.

In this article, we explore the implications of such a schema-creation process for asset pricing. If an investor analyses a firm for which she does not have a pre-existing schema, then she may use the schema of a similar firm that she had analysed earlier as a starting point and attempt to appropriately adjust it. How far the adjustment process goes depends on high tightly the resource constraint in the brain binds. For simple schemas, such as for a cow or a horse, the resource-constraint is not likely to be binding with full adjustment reached; however, for sufficiently complex schemas such as that of a firm, the resource constraint is expected to bind.

Research in brain sciences has established that there is brain specialization with different brain systems performing different tasks and competing for scarce resources that are allocated by a 'central executive system' (CES) located in the lateral prefrontal cortex (see Alonso et al (2014) and references therein). This suggests that, while modifying an existing schema to create a new one, each unit in a schema is exclusively worked on by a distinct system of neurons. Each system makes demands for resources with task performance dependent on resource allocation. Arguably, the two units in the schema of a firm are expected cashflows and the risk of the cashflows, with a different system of neurons working on each and making resource demands to CES. Given the central importance of expected cashflows in asset pricing (Basu 2013), and also because expected cashflow level is an input in any measure of risk (for example, volatility is based on deviations from the mean, so need

[6] van Kesteren et al (2012), Gilboa and Marlatte (2017).

to know the mean to calculate volatility), arguably, relatively more brain resource are allocated to the system of neurons working on expected cashflows. Formally incorporating this train of thought in asset pricing leads to some startling results and potentially resolves several key asset pricing puzzles with just one idea, including the equity premium puzzle. Related research includes Alonso et al (2014) who present a general model of resource allocation in the brain, and Siddiqi (2020) who present a modification of the capital asset pricing model when the brain is resource constrained.

2. Asset Pricing

We take the standard consumption-based asset pricing approach and add a twist to it: *schema-creation*. As standard, we assume that investor behavior is accounted for by a representative investor who maximizes utility over current and future consumption:

$$U(c_t, c_{t+1}) = u(c_t) + \beta E_t[u(c_{t+1})] \tag{2.1}$$

where c_t is consumption at t.

Using w_t to denote investor wealth at t, p_{it} to denote price of stock i at t, n_i for the number of shares of stock i in the portfolio, and x_{it+1} to denote the payoff from i at $t+1$:

$$c_t = w_t - \sum_i n_i p_{it}$$

$$c_{t+1} = w_{t+1} + \sum_i n_i x_{it+1}$$

The above utility maximization results in the following key asset pricing equation:

$$p_{it} = E_t\left[\beta \frac{u'(c_{t+1})}{u'(c_t)} x_{it+1}\right] = E_t[M_{t+1} x_{it+1}] \tag{2.2}$$

where $M_{t+1} = \beta \frac{u'(c_{t+1})}{u'(c_t)}$ is the stochastic discount factor/marginal rate of substitution. If the gross risk-free return is R_F, then it follows that: $E_t[M_{t+1}] = \frac{1}{R_F}$

(2.2) can be expanded as:

$$p_{it} = \frac{E_t[x_{it+1}]}{R_F} + Cov_t(M_{t+1}, x_{it+1}) \tag{2.3}$$

2.1 Schema Creation

When an investor analyses a firm for the first time, a schema for the firm may be created by modifying an existing schema associated with a similar firm that had been analysed earlier. As discussed in the introduction, such schema creation is a resource intensive process where finite brain resources are allocated across multiple tasks. As stock analysis is typically done at firm-level cashflows before scaling down to the level of an individual stock, we assume that a schema is created at the level of firm cashflows as well.

Generalizing from (2.3), the schema for firm-value is as follows:

$$Value = \frac{Expected\ Cashflows}{RiskFree\ rate} + Adjustment\ for\ Cashflow\ Risk$$

If an investor analyses a firm, s, for the first time, she may use the pre-existing schema of a similar firm, q (analysed earlier), as a starting point, and use brain resources in an attempt to appropriately adjust the schema.

Defining cashflows of firm q by π_q, and cashflows of firm s by π_s, the adjustments are given by:

$$E_t'[\pi_s] = E_t[\pi_q] - z_1 D_1 \tag{2.4}$$

$$Cov_t'(M_{t+1}, \pi_s) = Cov_t(M_{t+1}, \pi_q) - z_2 D_2 \tag{2.5}$$

where $D_1 = E_t[\pi_q] - E_t[\pi_s]$, $D_2 = Cov_t(M_{t+1}, \pi_q) - Cov_t(M_{t+1}, \pi_s)$, $0 \leq z_1 \leq 1$, and $0 \leq z_2 \leq 1$.

If the resource constraint is not binding then $z_1 = z_2 = 1$, and the pre-existing schema-units belonging to q are appropriately adjusted to create the new schema-units for s:

$$E_t'[\pi_s] = E_t[\pi_s] \quad \text{and} \quad Cov_t'(M_{t+1}, \pi_s) = Cov_t(M_{t+1}, \pi_s)$$

However, with a binding resource constraint, how the brain resources are allocated between the two schema-units matters. Given the central importance of expected cashflows in the schema (can't even begin to calculate covariance of cashflows without figuring out expected cashflows first), we make the reasonable assumption that more brain resources are allocated to the system of neurons working on expected cashflows. That is, we assume that $z_1 > z_2$. Without loss of generality, we set $z_1 = 1$. It follows that $z_2 = z < 1$.

Dividing (2.5) by the number of shares of s outstanding, n_s^*:

$$Cov_t'(M_{t+1}, EPS_s)$$
$$= Cov_t\left(M_{t+1}, EPS_q\right)\frac{n_q^*}{n_s^*} - z\left\{Cov_t\left(M_{t+1}, EPS_q\right)\frac{n_q^*}{n_s^*} - Cov_t(M_{t+1}, EPS_s)\right\}$$

where $EPS_s = \frac{\pi_s}{n_s^*}$ and $EPS_q = \frac{\pi_q}{n_q^*}$

The above can be simplified further as:

$$Cov_t'(M_{t+1}, EPS_s)$$
$$= Cov_t(M_{t+1}, EPS_s) + (1 - z)\left\{Cov_t\left(M_{t+1}, EPS_q\right)\frac{n_q^*}{n_s^*} - Cov_t(M_{t+1}, EPS_s)\right\}$$

Again, following the behavior of professional stock analysts, we define the notion of similar firms as:

1) In the same line of business

2) With similar price-to-earnings ratios (inclusive of dividends): $c_s \approx c_q = c$

It follows that:

$$Cov_t'(M_{t+1}, cEPS_s)$$
$$= Cov_t(M_{t+1}, cEPS_s)$$
$$+ (1 - z)\left\{Cov_t\left(M_{t+1}, cEPS_q\right)\frac{n_q^*}{n_s^*} - Cov_t(M_{t+1}, cEPS_s)\right\}$$

$$\Rightarrow Cov_t'(M_{t+1}, x_{st+1})$$
$$= Cov_t(M_{t+1}, x_{st+1}) + (1 - z)\left\{Cov_t\left(M_{t+1}, x_{qt+1}\right)\frac{n_q^*}{n_s^*} - Cov_t(M_{t+1}, x_{st+1})\right\} \tag{2.6}$$

where $x_{st+1} = p_{st+1} + d_{st+1}$ and $x_{qt+1} = p_{qt+1} + d_{qt+1}$

This approach captures two key features of resource allocation in the brain (see Alonso et al (2014)):

1) When a new schema is created by modifying an existing schema, the process is broken down into separate tasks, with each unit worked on by a separate system of neurons. Each

system communicates its resource requirements to CES, which allocates finite brain resources between systems.

2) The resource constraint is generally binding for complex schemas with task performance dependent on how much of resources are allocated to that particular task.

Substituting (2.6) in (2.3):

$$p_{st} = \frac{E_t[x_{st+1}]}{R_F} + Cov_t(M_{t+1}, x_{st+1}) + (1-z)\left\{Cov_t\left(M_{t+1}, x_{qt+1}\right)\frac{n_q^*}{n_s^*} - Cov_t(M_{t+1}, x_{st+1})\right\} \quad (2.7)$$

$$\Rightarrow E_t[R_{st+1}] - R_F = -\frac{Cov_t(M_{t+1}, x_{st+1})}{p_{st}E_t[M_{t+1}]}\left\{z + (1-z)\frac{Cov_t\left(M_{t+1}, x_{qt+1}\right)}{Cov_t(M_{t+1}, x_{st+1})}\frac{n_q^*}{n_s^*}\right\}$$

Substituting $Cov_t(M_{t+1}, x_{st+1}) = \rho_s\sigma(M_{t+1})\sigma(x_{st+1})$ and $Cov_t\left(M_{t+1}, x_{qt+1}\right) = \rho_q\sigma(M_{t+1})\sigma\left(x_{qt+1}\right)$ and simplifying:

$$\frac{E_t[R_{st+1}] - R_F}{\sigma(R_{st+1})} = -\frac{\rho_s\sigma(M_{t+1})}{E_t[M_{t+1}]}\left\{z + (1-z)e\frac{\sigma\left(n_q^* x_{qt+1}\right)}{\sigma(n_s^* x_{st+1})}\right\} \quad (2.8)$$

where $e = \frac{\rho_q}{\rho_s}$

(2.8) relates the Sharpe-ratio of stock s with volatility of the stochastic discount factor, $\sigma(M_{t+1})$.

As can be seen from (2.8), adjusting for schema-creation has added a new multiplicative term on the right-hand-side in the standard Sharpe-ratio expression of asset pricing. The term is:

$$f = z + (1-z)e\frac{\sigma\left(n_q^* x_{qt+1}\right)}{\sigma(n_s^* x_{st+1})}$$

(2.8) converges to the classical Sharpe-ratio expression if the resource constraint in the brain is not binding. That is, when $z = 1$.

The multiplicative term f does all of the heavy lifting in what follows. It is a weighted average of 1 and a ratio (standard deviation of firm q market cap divided by standard deviation of firm s market cap). Investor and analyst attention is highly asymmetric with most of the time spent on large, prominent firms (Fang and Peress 2009). Such prominent firms (with large market capitalisations) are expected to spawn schemas for other firms. Hence, $\frac{\sigma(n_q^* x_{qt+1})}{\sigma(n_s^* x_{st+1})} \gg 1$. This implies that $f \gg 1$.

2.2 The Equity Premium Puzzle

(2.8) provides a plausible quantitative solution to the equity premium puzzle (Mehra and Prescott 1985). In the US, historical equity premium has been between 4% to 8% with a standard deviation of around 16% on average (Cochrane 2017). Using 6% as the equity premium, the left-hand-side of (2.8) is 0.375. Using $\rho_s = -0.5$, (2.8) simplifies to:

$$0.75 = \frac{\sigma(M_{t+1})}{E_t[M_{t+1}]}\left\{z + (1-z)e\frac{\sigma\left(n_q^* x_{qt+1}\right)}{\sigma(n_s^* x_{st+1})}\right\} \tag{2.9}$$

Assuming power utility, and as standard practice, assuming lognormal consumption growth, it follows that:

$$\frac{\sigma(M_{t+1})}{E_t[M_{t+1}]} \approx \gamma\sigma(\Delta lnc)$$

where γ is the coefficient of risk-aversion.

In the US post war data, aggregate consumption growth has been around 2% (Cochrane 2017). Plugging these in (2.9):

$$0.75 = \gamma 0.02\left\{z + (1-z)e\frac{\sigma\left(n_q^* x_{qt+1}\right)}{\sigma(n_s^* x_{st+1})}\right\}$$

$$\Rightarrow 37.5 = \gamma\left\{z + (1-z)e\frac{\sigma\left(n_q^* x_{qt+1}\right)}{\sigma(n_s^* x_{st+1})}\right\} \tag{2.10}$$

Using the constituent stocks in the S&P 500 index as a proxy for firms that spawn the schemas for other firms, the average market cap of a q firm is around \$55 Billion (Dec. 2019). With standard deviation of market cap, conservatively estimated to be 10%, $\sigma\left(n_q^* x_{qt+1}\right) = \$5.5$ Billion. Excluding the top 500 firms, the average market cap of the remaining 1900 firms in NYSE is no more than \$3 Billion (Dec. 2019). With standard deviation of market cap at around 10%, $\sigma(n_s^* x_{st+1}) = \$0.3$ Billion. Setting $e = 2$, and $z = 0.5$, it follows that $\gamma \approx 2$. Hence, the observed high equity risk-premium can be reconciled with the consumption-based model with low risk-aversion when asset prices are adjusted for

Table 1

Risk-Aversion Coefficient and the Tightness of the Resource Constraint in the Brain

Risk-Aversion Coefficient (γ)	Resource Constraint Parameter (z)
1.02	0.0
1.13	0.1
1.27	0.2
1.44	0.3
1.67	0.4
1.99	0.5
2.46	0.6
3.21	0.7
4.61	0.8
8.21	0.9
37.5	1.0

resource allocation in the brain. A key parameter here is how tightly the resource constraint binds with a tighter resource constraint (low z) lowering the risk-aversion needed to reconcile theory with data. Table 1 shows this relationship for various levels of tightness. Table 1 shows that when the resource constraint in the brain does not bind $(z = 1)$, we are back to classical (schema-free) asset pricing approach with a high risk-aversion coefficient is needed (37.5) to match theory with data. On the other hand, when the resource constraint is at its tightest $(z = 0)$, the level of risk-aversion coefficient needed is quite small (1.02). With the resource constraint biding at 0.5 to 0.7 level, the required risk-aversion coefficient is in 1.99 to 3.21 range.

2.3 Equity Risk-Premium is Countercyclical

Empirical evidence shows that the equity risk premium is countercyclical. For example, Harvey (1989) showed that US equity risk premia are higher at business cycle troughs than they are at peaks. Similar results are reported in Bekaert and Harvey (1995), He, Kan, Ng and Zhang (1996) and Li (2001) among others. With asset pricing adjusted for resource allocation in the brain, the countercyclical nature of the equity risk-premium can be seen from (2.8) by realizing that $f = z + (1-z)e\frac{\sigma(n_q^* x_{qt+1})}{\sigma(n_s^* x_{st+1})}$ is countercyclical. This is because smaller firms are hit harder in recessions when compared with larger firms (Lai et al 2016, Sahin et al 2011). Consequently, the market capitalizations of smaller firms generally decline by a larger factor. Using g_q and g_s to denote the factors by which market capitalizations of q and s firms decline: $g_s > g_q$.

It follows that: $\frac{\sigma\left(\frac{n_q^* x_{qt+1}}{g_q}\right)}{\sigma\left(\frac{n_s^* x_{st+1}}{g_s}\right)} > \frac{\sigma(n_q^* x_{qt+1})}{\sigma(n_s^* x_{st+1})}$ which implies that f is larger in bad times.

2.4 The Size Effect

The size effect can be seen directly from the Sharpe-ratio expression derived under the schema-creation approach (equation 2.8):

$$\frac{E_t[R_{st+1}] - R_F}{\sigma(R_{st+1})} = -\frac{\rho_s \sigma(M_{t+1})}{E_t[M_{t+1}]} f$$

where

$$f = z + (1-z)e\frac{\sigma(n_q^* x_{qt+1})}{\sigma(n_s^* x_{st+1})}$$

All else equal, smaller the market capitalization, $n_s^* x_{st+1}$, larger the value of $\frac{\sigma(n_q^* x_{qt+1})}{\sigma(n_s^* x_{st+1})}$. Hence, f is higher for a small cap stock when compared with a large cap stock. Hence, the size effect emerges naturally.

2.5 The Value Premium

Value premium is the robust empirical finding that stocks with low price to fundamentals outperform stocks with high price to fundamentals. In the approach developed here, value premium also emerges quite naturally. Two stocks with the same fundamentals may have different prices if the pre-existing schemas that were modified to create the new schemas for the two stocks are different. Consider two stocks, s and s', that have the same cashflow fundamentals: $E_t[x_s] = E_t[x_{s'}]$ and $Cov_t(M_{t+1}, x_s) = Cov_t(M_{t+1}, x_{s'})$.

If $p_s < p_{s'}$ then it must be:

$$\left|Cov_t(M_{t+1}, x_q)\frac{n_q^*}{n_s^*}\right| > \left|Cov_t(M_{t+1}, x_{q'})\frac{n_{q'}^*}{n_{s'}^*}\right|.$$

$$\Rightarrow \frac{\left|Cov_t(M_{t+1}, x_q)\frac{n_q^*}{n_s^*}\right|}{|Cov_t(M_{t+1}, x_s)|} > \frac{\left|Cov_t(M_{t+1}, x_{q'})\frac{n_{q'}^*}{n_{s'}^*}\right|}{|Cov_t(M_{t+1}, x_{s'})|}$$

$$\Rightarrow e_s \frac{\sigma(n_q^* x_q)}{\sigma(n_s^* x_s)} > \; e_{s'} \frac{\sigma(n_{q'}^* x_{q'})}{\sigma(n_{s'}^* x_{s'})}$$

$$\Rightarrow f > f'$$

Hence, f is larger for the stock with lower price to fundamentals. This is the value premium.

2.5 The Momentum Effect

Momentum effect refers to the empirical finding that stocks that have done well (poorly) recently continue to do well (poorly) over short horizons into the future (6 months or so) (Jagadeesh and Titman 1993). An intriguing explanation arises for momentum effect with schema creation. As schema-creation is a resource intensive process, schemas, once created are unlikely to be changed, unless there is are reasons for change such as many large prediction errors. It is easy to see that using schemas generate stock price predictions that are rank-order correct (one can see this directly from 2.7). That is, more risky stocks are priced lower than less risky stocks. This is a pretty good showing given the resource constraint in the brain, not only leading to economizing of resources between units within a schema, but also across schemas of various stocks.

However, unexpected superior performance of a small set of stocks may lead to a re-allocation of more brain resource towards their schemas. For example, a positive return shock (momentum winners) may attract more attention from investors. Higher attention may lead to more brain resources being directed to the schemas of such stocks, pushing up z. As z rises, stock price rises (when payoff and discount factor are negatively correlated as expected for most stocks) in (2.7). This is the momentum effect.

If momentum effect is indeed associated with more brain resources being directed to winners to update their schemas, then it immediately follows that momentum effect must be negatively correlated with both value and size effects. This is because a higher z, which gives rise to momentum, makes both value and size weaker, as f falls when z rises. Hence, the schema adjusted model can be falsified empirically if these negative correlations are not observed in the data. Empirical evidence has uncovered such negative correlations (Asness et al 2013, Rabener 2017), which are quite strong for value-momentum pair.

3. Conclusions and Discussion

This article shows that one, relatively simple adjustment, to the standard asset pricing approach goes a surprisingly long way. The adjustment is based on the findings from brain sciences that, when information reaches the brain, a pre-existing knowledge structure or schema is first activated, which influences information absorption. The process of schema-construction is a resource intensive process, which uses a pre-existing schema as a starting point and attempts to adjust the relevant units by spending finite brain resources. We apply the same approach to the thinking process of investors trying to work out the worth of various stocks. We show that with a binding resource constraint, a new multiplicative term emerges on the right-hand-side of the standard Sharpe-ratio expression in asset pricing. This new term provides a unified explanation for the equity premium puzzle, generates countercyclical equity premia, and gives rise to size, value, and momentum effects. A novel prediction of the approach is negative correlation of momentum with value and size.

References

Alonso, Brocas, and Carrillo (2014), "Resource allocation in the brain", *Review of Economic Studies*, Vol. 81, pp. 501-534.

Anderson, J. R. (2000). Cognitive Psychology and Its Implications (5th ed.). New York, NY. Worth Publishers.

Asness, Tobias, and Maskowitz (2013), "Value and Momentum Everywhere", *Journal of Finance,* Vol. 68, Issue 3, pp. 929-985.

Basu, Duong, Markov and Tan (2013), "How Important are Earnings Announcements as an Information Source", *European Accounting Review*, Vol. 22, pp. 221-256.

Bekaert, G., and Harvey, C. (1995), "Time-varying world market integration", *Journal of Finance*, Vol.50, No.2, pp.403-44

Cochrane, J. (2017), "Macro-Finance", *Review of Finance,* Vol. 21, Issue 3, pp. 945-985.

Fang and Peress (2009), "Media coverage and the cross section of stock returns", *Journal of Finance*, Vol. 64, pp. 2023-2052.

Gilboa, A., and Marlatte, H. (2017), "Neurobiology of schema and schema mediated memory", *Trends in Cognitive Science*, Vol. 21, pp. 618-631.

Hampson, P. J. & Morris, P. E. (1996) Understanding Cognition. Cambridge, MA. Blackwell Publishers.

Harvey, C. R. (1989), "Time-varying conditional covariances in tests of asset pricing models", *Journal of Financial Economics*, Vol.24, pp. 289-317.

He, J., Kan, R., Ng, L., and Zhang, C. (1996), "Tests of relations among market wide factors, firm-specific variables and stock returns using a conditional asset pricing model', *Journal of Finance*, Vol. 51, No.5, pp.1891-1898.

Lai, Saridakis, Blackburn, Johnstone (2016), "Are HR responses of small firms different from large firms in times of recessions?", *Journal of Business Venturing,* Vol. 31, Issue 1, pp. 113-131.

Li, Y. (2001), "Expected returns and habit persistence", *Review of Financial Studies*, Vol.14, pp. 861-99.

Mehra and Prescott (1985) "The Equity Premium: A Puzzle", *Journal of Monetary Economics,* Vol. 15, Issue 2, pp. 145-161.

Ohki and Takei (2018), "Neural mechanisms of mental schema: a triplet of delta, low beta/spindle and ripple oscillations", *European Journal of Neuroscience,* Vol. 48, pp. 2416-2430.

Rabener, N. (2017), "Factors: Correlation Check", Available at https://www.factorresearch.com/research-factor-correlation-check

Sahin, Cororaton, Kitao, and Laiu (2011), "Why small business were hit harder by the recent recession," *Current Issues in Economics and Finance,* Federal Reserve Bank of New York, Vol. 17.

Siddiqi, H. (2020), "Resource Allocation in the Brain and the Capital Asset Pricing Model", MPRA paper 100250.

Siddiqi, H. (2020), "Resource Allocation in the Brain and the Capital Asset Pricing Model", Available at https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3591086

Spalding, Jones, Duff, Tranel, and Warren (2015), "Investigating the Neural Correlates of Schemas: Ventromedial Prefrontal Cortex Is Necessary for Normal Schematic Influence on Memory", *Journal of Neuroscience,* Vol. 35, pp. 15745-15751.

Sweegers, Coleman, van Poppel, Cox, and Talamini (2015), "Mental schemas hamper memory storage of goal-irrelevant information", *Frontiers in Human Neuroscience*, Vol. 9, pp. 6-29.

van Kesteren MT, Ruiter DJ, Fernandez G, Henson RN (2012), "How schema and novelty augment memory formation", *Trends in Neuroscience*, Vol. 35, pp. 211–219.

van Kesteren, Rijpkema, Ruiter, Richard, Morris, and Fernández (2014), "Building on prior knowledge: Schema-dependent encoding processes relate to academic performance", *Journal of Cognitive Neuroscience*, Vol. 26, Issue 10, pp. 2250-61.

van Kesteren MT, and Meeter (2020), "How to Optimize Knowledge Construction in the Brain", *Science of Learning,* 5, Article Number 5.